A robust algorithm based on a failure sensitive matrix for fault diagnosis of power systems: An application on power transformers

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Abstract: *In this paper, a robust algorithm for fault diagnosis of power system equipment based on a Failure-Sensitive Matrix (FSM) is presented. FSM is a dynamic matrix structure updated by multiple measurements (on-line) and test results (off-line) on the systems. The algorithm uses many different artificial intelligence (AI) and expert system (ES) methods for detecting the location of faults, emerging failures and causes of failures adaptively. In this algorithm, all data, obtained from power transformer which have various nonlinear input and output parameters is processed using a parallel matrix structure of FSM to reach a global solution quickly. The parameters of a power transformer are used to verify the algorithm under four operating conditions simulated in the MATLAB®-Simulink program. The obtained results show that the algorithm is convenient for determining the incipient failures on the system which consists of multi-parameters.*

Keywords: *Failure sensitive matrix, fault diagnosis, expert system, monitoring, transformer.*

I. Introduction

Diagnosis and early detection of faults in a system help to avoid the occurrence of abnormal events and to reduce production loss. [1-4]. In recent years, there has been an increasing interest in fault detection as a result of the increased degree of automation and the growing demand for higher performance, efficiency, reliability and safety in industrial power systems. Most of the researchers have focused on finding incipient faults in the systems before they occur, and today's technology allows the monitoring of power systems through many different sensors. In industry, there is a lot of monitoring equipment developed for specifically to detect incipient faults that can occur in the systems [5-8]. However, it is important to compose evaluations based on data obtained from the system by various sensors. For this purpose, various methods such as expert systems, heuristic algorithms, fuzzy logic, artificial neural-network, genetic algorithm and their hybrid models are used to evaluate the obtained data for fault diagnosis and early detection [9-15].

On the other hand, industrial complex systems have many dynamic factors such as various components, sub-systems, the environment and people. In these systems, any single fault may have multiple propagation paths, which could eventually lead to catastrophic accidents [9,12,16]. In these systems, monitoring data obtained from all systems should be evaluated quickly. Then, according to the results, technical maintenance procedures must be carried out to avoid any potential faults in the system, and the resulting economical costs such as uneconomical operating conditions, unexpected equipment breakdown, unplanned outage and high insurance premiums. In addition, the diagnosis system extends the life of the system by ensuring proper operation of, and improvement in the system performance, improved reliability, as well as plant availability.

However, early detection and diagnosis of incipient faults with their causes are difficult since the complex industrial systems have a number of factors including output and input elements. For this purpose, an algorithm has been developed using different mathematical rules called a Failure-Sensitive Matrix (FSM) to evaluate the various parameters and to accelerate the process of early fault detection in this paper. The algorithm also correlates between the parameters and fault's symptoms using artificial intelligence (AI) and expert system (ES) adaptively.

In general, fault diagnostic methods can be classified into two categories, model-based and data-driven as shown in Figure 1. In the model-based approach, fault detection and diagnosis systems can be classified as qualitative or quantitative. Quantitative models are expressed in terms of mathematical functional relationships between the input and output of the system. In contrast, in the qualitative model equations these relationships are expressed in terms of qualitative functions centered on different units in a process [17-19]. In the data driven approach, methods that do not assume any form of model information are used, and rely only on previously processed data. The data-driven approach assumes only the availability of large amounts of previously processed data. The data can be transformed and entered as earlier information in a diagnostic system in different ways.

All fault diagnosis models have to adapt a common system consisting of three subtasks: to detect the presence of faults in the system through monitoring, determine their locations, and estimate their severity. In general, the following definitions are expressed in the literature [20,21].

☐ Fault detection: To make a binary decision whether everything is fine (nominal) or something has gone wrong (off-nominal).

☐ Fault isolation: To determine the location of the fault, i.e., to identify which component, sensor, or actuator has become faulty.

☐ Fault identification: To estimate the severity, type, or nature of the fault.

A monitoring system is necessary to determine the relationship between failure and symptoms as described by Füssel, shown in Figure 2 (a) physical system and (b) diagnosis system as well as to do condition- based maintenance [22]. The condition-based maintenance strategy monitors the condition of the equipment by measuring and analyzing key parameters for the purpose of detecting changes, which may indicate damage or degradation, and recommends optimal maintenance actions.

Today's industrial systems have many non-linear parameters related to multiple input and output. Therefore, evaluation and determination of a fault in these complex systems is not easy for experts. For this reason, different software based on monitoring and diagnosis algorithms have been developed by experts. The programs are widely and easily used by engineers to enter input data according to their experience and heuristic knowledge about the system. Various techniques have been reported for fault diagnosis and classification in industrial systems. Widely used techniques are the neural network approach, fuzzy, fuzzy neural network, expert systems, heuristic methods and unique methods such as decision tree, fault tree, Petri nets, fuzzy Petri nets, and Bayesian networks. There are advantages and disadvantages of the methods specified in relation to each other depending on the application field such as data evaluation, fault identification, classification, forecasting, optimization, and planning process [23-32]

As mentioned above, all of these methods have advantages and disadvantages according to each other depending on their field of application such as data evaluation, fault diagnosis, identification, classification, forecasting, optimization, and planning process. Today, the same methods are used together as hybrids to get robust results for fault diagnosis in industrial power systems. In large industrial power systems, the diversity and complexity of problems are on a large scale. For this reason, the number of fault diagnosis methods used increases. In this case, the system is divided into sub-systems and analyzed separately. This is an application that is time-consuming and difficult. Also, fault probability results that are produced with the selected method/s will be limited to good results related to the method/s, but not cover the best global results for the whole system. The developed method, FSM aims to eliminate such problems.

In this study, the algorithm was tested by various faults made to occur deliberately on a test transformer designed using a DAQ card and program interface. First, outputs of the system are defined according to the limit values and then they integrated into the FSM matrix which combines different monitoring parameters evaluated by expert system using by interface program. The proposed method and technical details are presented following sections. Power transformer prototype structure and instrumentation details described in the Appendix.

II.   The proposed method

In recent applications, mathematical algorithms have been combined with artificial intelligence techniques and methodologies to improve effective analysis. FSM opens a new dimension on fault diagnosis by evaluating multi-input and multi-output data obtained from the complex and large industrial systems. FSM is created by multiplying coefficient matrices and varies with time according to monitoring parameters in dynamic systems. A fault diagnosis algorithm based on FSM is the common interface to combine different monitoring parameters which could be evaluated together by using selected AI and ES methods.

The characteristics of the monitoring systems are different, and some of the instruments have evaluation software using their own algorithms that need an expert system to interpret, test, and/or measurement data [11,23]. Separate evaluation of all test and measurement (T&M) data is a disadvantage in large and complex systems. But evaluation of combined data obtained from all of the tests and measurements (T&M) systems on a single interface gives more effective results for detecting the location of faults, emerging failures and causes of failures. For this reason, the scheme developed a fault diagnosis algorithm based on FSM that consists of five phases; a) On-line and off-line data acquisition (T&M groups), b) Expert system evaluations, c) Creation of coefficient matrices, d) Generation of the fault sensitive matrix and e) Determination of defective components of the system as shown in Figure 3. Both the data taken from the continuous system and the FSM are updated by time intervals. And the processing time is fast due to the nature of the parallel computation caused by matrix structures.

2.1 Failure-sensitive matrix (FSM)

FSM is the common interface to combine different data taken from monitoring equipment on the system and to evaluate all together. FSM is a matrix created by sequential scalar multiplying of coefficient matrices and varies with time according to the monitoring parameters in dynamic systems. In Figure 3, the structure of the FSM is simply presented. Each matrix belongs to a test and measurement group. These sub-matrices consist of coefficients and each coefficient row vector [1xn] is created with an algorithm developed by human experts using AI and ES methodologies.

Although coefficient vectors are similar to fuzzy rule base, as a whole, matrices should not be confused with it. Expert systems, fuzzy logic, artificial neural-network, heuristic algorithms, and their hybrid models can be used in the process of creating coefficient vectors. Each coefficient symbolized by C has a fault weight depending on the relationship between fault types and monitoring parameters. Decision vector [1xn] means fault probabilities are according to only one test and/or measurement data. In this way, monitoring equipment will be used to detect ratings of failure for the other fault types in addition to its main function.

In the structure in Figure 3, the inception matrix size is set on the basis of maximum number of instruments in a T&M group (rows) and number of fault types (columns). In large and complex systems, due to the fact that the number of rows and columns depend on the number of components, the size of the FSM will be extensive. The matrices which are obtained from evaluation of the measurement data are multiplied element-by-element. Therefore, generated coefficients

should be equal or greater than one{ $\alpha \propto C \Rightarrow \forall C \geq 1$ }. Alpha is $1 \leq \alpha$ and $\alpha \in \mathsf{N}^+$, $\mathsf{N}^+ = \{1, 2, 3, \mathsf{K}\}$ positive integer. Table 1 gives us the linguistic terms to determine relationships between monitoring parameters and fault types for all methods used in the data evaluation stages.

The intersection matrix, which is formed by component fault types and monitoring

(M&T)   decision   vectors $i = 1\mathsf{K}\,n, j = 1\mathsf{K}m$ *and* $i, j \in N^+ \therefore$

$\mathrm{MAT}_k[i : \_\,] \perp \mathrm{MAT}_k[\_\, : j]$ $\qquad :\Leftrightarrow C_{ij}$, defines the relationship between T&M results

and fault types of related components. Where, MAT_k is the matrix consisting of rows (n)

and columns (m). Each coefficient, C_{ij} is weighted by the greatest value obtained in result evaluations according to the fault types. It cannot exceed the limit value, which is defined as Equation (1):

$$\{C_{ij}^{(k)} \in MAT_k[nxm] : \forall C_{ij} < (5\alpha)^k_{(k)}\}. \tag{1}$$

Where k is the number of scalar multiplications computed. The equation of sub-sensitive matrices consists of the number k, which is the same number as the T&M groups. And the equations are written as follows:

$$\left. \begin{array}{l} MTRX\,(Ones)[nxm]\,.\,\cdot\ MATRIX\,(C_1)[nxm] = MAT\,(\mathrm{Pr}_1)[nxm] \\[4pt] MAT\,(\mathrm{Pr}_1)[nxm]\,.\,\cdot\quad MATRIX\,(C_2)[nxm] = MAT\,(\mathrm{Pr}_2)[nxm] \\[2pt] MAT\,(\mathrm{Pr}_2)[nxm]\,.\,\cdot\quad MATRIX\,(C_3)[nxm] = MAT\,(\mathrm{Pr}_3)[nxm] \\[2pt] \qquad\qquad \mathsf{M}\ \ \mathsf{M} \\[2pt] MAT\,(\mathrm{Pr}_{k-1})[nxm]\,.\,\cdot\ MATRIX\,(C_k)[nxm] = MAT\,(\mathrm{Pr}_k)[nxm] \end{array} \right\} \tag{2}$$

Where $MTRX\,(Ones)[nxm]$ is an inception matrix and $MATRIX\,(C)[nxm]$ refers to the fault probability coefficient matrix consisting of decision row vectors. $MAT\,(Pr)[nxm]$ is the fault probability matrix created according to only one T&M group result. The last matrix, $MAT\,(\mathrm{Pr}_k)[nxm]$ is a failure-sensitive matrix including the effects of all monitoring data obtained from the complex system by the different T&M groups. Where notation $(.\,\cdot)$ refers to scalar multiplication between matrices. Sometimes, the row numbers in the matrix cannot be equal to each other because of different numbers of T&M groups. In this case, the unit row vector requires equalization of the matrices.

Equation (3) can be used to find the rating of fault probabilities after the scalar multiplications of the coefficient matrices.

$$Faults\,[1 \cdot m] = \left| \sum_{i=1}^{n} MAT_{(k_1)}[i:1], \sum_{i=1}^{n} MAT_{(k_2)}[i:2], \mathsf{L}, \sum_{i=1}^{n} MAT_{(k_m)}[i:m] \right| \tag{3}$$

Where, $Faults\,[1xm]$ is a vector and consists of the cumulative totals of each column related to fault type. The vector gives us all the probabilities of current fault types. The occurrence of all failures is not possible at the same time and/or at an equal rate. Therefore, the Equation (4) is used to find the maximum probability of faults ($Cfj\%$) in the system.

$$Cf_i\% = \frac{\max(Faults[1xm])_i^{\frac{1}{(k-Cr_j)}}}{[TpV]_i} \ x\ 100. \tag{4}$$

Where, TpV exponential is a value of maximum probability for the jth fault type, Crj correction coefficient of the jth fault type which is an defined as $\{Cr_j \in \mathsf{N} : 0 \leq Cr_j \leq k\}$. In case of the absence of significant relationships between T&M results and fault types, the coefficient values are defined as one, ($Cij := 1$). The exponential correction coefficient Crj is used to correct the result in these situations.

III.   Modeling and verifying of the algorithm

In order to verify and show the robustness of the algorithm, power transformer equipment has been preferred as a complex system in the power industry. Power transformers used in power plants can be monitored and examined in aspects such as loadability, life extension, aging, dielectric degradation, dielectric breakdown, arcing, discharges, contact failures, cooling performance, etc. At this stage, T&M systems that will be used for related applications have been chosen, and their input parameters have been modeled in the MATLAB®. The T&M systems should be grouped according to the degree of closeness when considering the fault types. In Figure 3 there are four groups of T&Ms which have different main tasks. The task of each T&M group and the evaluation method used to calibrate the coefficients of FSM are described.

T&M methods and related parameters have been evaluated by considering the fault types. In the case of continuous operation of the algorithm, all the T&M parameters would be continuously variable. But to assess the current processing performance of the algorithm, the parameters which take a certain time (t_n) are used in this section as shown in Figure 3. In application, the obtained data are updated for certain periods. Thus when the system is out of service, the last FSM results in memory can be accessed.

As shown in Figure 4, the data is obtained using National Instrument DAQ-16, 1.25 MS bit/s resolution from the system which has different outputs. Because the DAQ card has a (0-10V) analog input range, the outputs must be normalized the range of value. For this purpose, a pre-circuit card is designed to amplify and to normalize the electrical signal transferred to the DAQ card. Before creating of the FSM matrix, to determine the limit value of the each input and considering the faults the expert systems, fuzzy logic tools, the program loops and fault tree are used.

T&M-1: Dissolved gas rates;

Dissolved gas analysis (DGA) is the most important tool in determining the condition of a transformer. The dissolved gas analysis (DGA) is carried out on the aged samples to predict the incipient faults and can identify deteriorating insulation and oil, overheating, hot spots, partial discharge, and arcing [33-38]. The expert systems combined with the fuzzy logic incorporate the expertise and experience of the diagnostic experts into the systems in the form of 'if-then' rules. The knowledge or diagnostic criteria extensively used by the utilities, such as the key gas method, Duval triangle, the Dornenburg and the Rogers gas ratio methods, in accordance with the standards IEC 60599 and IEEE C57.104 have served as the framework of the expert diagnosis system [39-41].

T&M-2: Current, Voltage, CO_2/CO rate;

Loadability of the transformer is continuously monitored with SCADA systems in modern power technologies. Loadability gives the same information as power transformers, such as power demand and life loss information according to time. Some evolving faults may be caused by overloading. But to know that, other symptoms should be closely monitored. In this content, the second T&M group (CO_2/CO rate measurement) gives the information about isolation conditions, aging acceleration, temperature, loadability, etc. IEEE Standard, C57.104 gives status conditions based on the accumulated values of CO_2 and CO [40]. ANN is the most appropriate method for evaluation of T&M-2 data.

T&M-3: Temperatures (ambient, average and top oil temperatures);

One of the most important parameters governing a transformer's life expectancy is the hottest spot temperature (HST) value. Hot spot insulation temperature represents the most important factor that limits a transformer from loading [42]. The hot-spot temperature has to be under a prescribed limit value. A cumulative effect of insulation aging, depending on time change of hot-spot temperature, should be less than a planed value. That is why it is important to know the hot-spot temperature at every moment during real transformer operations under the conditions of variable loads and ambient air temperature [43-46]. The generally accepted relationship of thermal aging properties of insulation material is described by the Arrhenius Reaction Rate Law [47]. The IEEE C57.91-1995 and IEC60076- Part.7 standards give an expression for the LOL (Loss of Life) of mineral oil cooled power distribution transformers. [48-50]. Artificial neural networks (ANN) are presently established as a useful and very promising tool, in particular those of a nonlinear dynamic system model [38,51].

T&M-4: Furanic compounds and power factor;

Power factor testing is important to determine the insulation condition of transformers because it can detect the insulation integrity in winding, bushing, arrester, tank, and oil [52]. Transformer insulation is universally made from a combination of cellulose paper or pressboard, fully impregnated with insulating oil. Overheating, oxidation, acids, and decay caused by high moisture with oxygen accelerate the destruction of insulation and form furanic compounds. Normal deterioration of paper is characterized by the rate of furans evolution as 50-90 ppb. But large amounts of furans can be generated when the temperature is above 120-130 °C. [53]. The furanic compounds analysis reveals the rate of insulating paper degradation of the equipment, and it directly projects the expected life [53,54]. Another test, called the power factor, is an effective way to detect defective electrical equipment insulation. The results of the overall power factor tests on power transformers reflect the insulation conditions of the windings, barriers, tap changers, bushings and oil. The power factor is the ratio of the capacitive or 'charging' current (measured in volt-amperes) to resistive or 'leakage' current (measured in watts) [52,55]. In this section, the fuzzy rule based approach is used for the evaluation of input data.

Fault types have been categorized as follows;
Fault type 1: Overloading, high power loss,
Fault type 2: Partial discharge,
Fault type 3: Breakdown, arcing,
Fault type 4: Insulating degradation, aging,
Fault type 5: Cooling problem,
Fault type 6: Component fault, connection failure,

In Table 2, for the verification of the algorithm, the conditions of four different instances are considered. These conditions are based on T&M, regardless of the fault types. The fault in the system has already been cleared as a cooling problem, as stated I^{th}, IIth and IIIth conditions except IVth condition. But T&M data obtained from the system or

interpretation of sensor information might not be reliable. On this basis, IIth, IIIth and IVth conditions have been prepared for testing the robustness of the algorithm. All conditions and decision vectors are shown in Table 2.

In this examination of the fuzzy method, rule based approach and ANN are recommended for determining the coefficients according to the T&M parameters. Generated coefficients, which are shown as a row vector determined by a preferred expert system, are combined as only one matrix structure in Table 2. The T&M group numbers are not equal to each other, so in this case a command can be written "MAT (n, :) =1" for the equalization of a related matrix in MATLAB®. Matrices sizes should be equal to the matrix belonging to the largest T&M group as shown in Equation (5).

$$FSM[4\cdot 6]= \begin{vmatrix} C & L & C_{1,6} \\ MAT_{(1)} & O & \vdots \\ c_{4,1} & L & \ddots \end{vmatrix} \cdot MAT_{(2)} \begin{vmatrix} & L & C_{1,6} \\ C & O & M \\ \vdots & L & C_{4,6} \end{vmatrix} \cdot MAT_{(3)} \begin{vmatrix} & L & C_{1,6} \\ C & O & \vdots \\ \vdots & L & C'_{4,6} \end{vmatrix} \cdot MAT_{(4)} \begin{vmatrix} & L & C_{1,6} \\ C & O & M \\ Lc & & \ddots \end{vmatrix}$$

Actually, each matrix indicates fault probabilities specifically related to the T&M group. All T & M systems should be considered as a whole, to   get the most accurate result of fault diagnosis. The last matrix, called   FSM, is formed through scalar multiplications of sub-matrices to ensure this validity. FSM is stated in an algorithm as $MAT (\Pr_k)$ and to find out any fault probabilities in the system, the command should be written confirming Equation (2) in the algorithm. All procedures according to these results are shown as bar graphs and all bar graphs indicated by 'last graph (d)' indicate the last matrices which were created by the recent scalar multiplication as shown Equation (6) in the algorithm for all of the figures.

$$Faults[1\cdot 6] = \begin{vmatrix} \sum_{n=1}^{4} FSM_4 \,_{(1}\,[n:1], & \sum_{n=1}^{4} FSM_4 \,_{(2)}\,[n:2], & \mathsf{K}, & \sum_{n=1}^{4} FSM_4 \,_{(6)}\,[n:6] \end{vmatrix} \qquad (6)$$

Hence, Cf_j gives the greatest fault probability in Equation (7). In this example Crj is taken as zero '0' because all T&M information has a certain amount of relationships by fault types.

$$Cf_i \% = \frac{max(\; Faults \; [1x6] \;)_j}{[TpV]_i}^{1/(4-Cr_j)} \quad x \; 100 = \; Fault \; probabilit \; y\% \qquad (7)$$

All results produced by FSM are interpreted by the specific levels of bandwidth. When the fault probability value is $0\% <_{fj} < 40\%$, the system can be assumed to be in secure region. If the value is between $40\% < _{fj} < 60\%$, the system should be observed.
If the value is between $60\% < _{fj} < 100\%$, the system is operating dangerously, and an operation may be required.

The data obtained from the system using sensors is normalized and graded from best to worst considering fault types. The outputs of the sensors are different from each other. For instance, water content of the paper less than 0.5 ppm is expected value, 0.5 ppm-2 ppm is permissible and values higher than 2 ppm is unacceptable. The other important parameter of the power transformer is temperature and it has limit values according to the IEEE standard, such as hot spot temperature is 110 °C, planned overloading temperature is 130 °C. Therefore, the obtained data is normalized using the same base value and five different risk levels as shown in Figure5.

In this study, the algorithm was tested and verified by various failures caused intentionally in laboratory. In addition, operations of the sensors located in application circuit are checked during the experiments.

Generally, result graphs show the fault probabilities as a percentage, and while the red bar indicates the maximum possible faults, the blue bar indicates incipient failures. But in addition to this, it may indicate a defect in the T&M system or evaluation process. If all the graphs indicate only one fault possibility, the result is good and reliable. But sometimes the results of T&M may be defective or an expert's know-how/database may not be enough to write the correct algorithm related in the T&M group. FSM is consistently reliable against such disturbances. Even if some evaluation results in the matrices indicate different fault possibilities contrary to others, FSM can discover the correct result on a global level and these situations are shown in Table 3. The FSM results of the overall fault situations are determined in a range as shown Table 4. This evaluation results are valid for the continuous case of each fault condition. For this reason, the results vary in a certain bandwidth according to the severity of the fault/s.

**Condition I:** As mentioned in Table 2, the cooling system is faulty on the power transformer, and in reality, this fault is possible under all conditions except the condition IV. The data obtained from the system using T&M systems and evaluations of these data are reliable. So the obtained results which are shown in Figure 6 are reliable, too. Fault type 5 has emerged, which is shown as a red bar in Figure 6. In Figure 6 (a), (b) and (c) indicate probabilities of the fault types according to the processing of first, second and third T&M groups, respectively. Figure 6 (d) shows the results of the fault probabilities according to the processing of the last matrix called FSM.

**Conditions II and III:** Conditions II and III indicate that the T&M system is faulty. In condition II, only one T&M of the group is not reliable or data evaluation is not correct. In condition III, a group of T&M are not reliable. In addition to the actual reality fault, show by the red bar, the other fault probability, shown by the blue bar, which is not correct, is shown in

Figure 7 (a), (b), (c) and (d) respectively. The algorithm has discovered the actual fault using the FSM approach. The fault type 2 should be observed because of the higher level of security. The functioning of the algorithm could be controlled by the experts. Figure 7 (b) is different from (a), (c) and (d) in terms of fault type 2. In this examination, it is clear that the T&M system appears to be faulty or data evaluations are not correct. This is an advantage of the algorithm: to determine if the T&M equipment is faulty. It is important to develop the evaluation process for the fault diagnosis system.

**Condition IV:** Condition IV indicates that the T&M system or data evaluations are shown in Figure 8 (a), (b), (c) and (d) respectively. There is a faulty situation, because power transformer systems do not have any actual fault. Except for Figure 8 (b), the others provide reliable results. But the algorithm still reaches a global outcome as shown in Figure 8 (d).

IV.   Conclusions

In this study, a robust fault diagnoses and evaluation algorithm based on the FSM structure was presented. The most important advantage of FSM is that it is an interface which works with ES and AI. For this reason, most suitable ES and AI applications for the system can be used without any amount or type of restrictions. The processing times of FSM and expert system are evaluated separately since it is affected by expert system. Therefore, FSM has matrix structure and it is designed by different from expert system to obtain rapid response.

Thus, it is possible to get a valid evaluation from the data obtained. The FSM is not affected negatively when the number and type of T&M are increased. On the contrary, these increases provide more accurate and reliable results for FSM. This results in an increase in the utility of fault diagnoses based on FSM in large and complex systems. Since data obtained from T&M systems and evaluation results of specialist systems is processed in a parallel manner through use of the matrix structure of FSM, the operation time is fast (almost the time a matrix multiplication). FSM can be defined as a hybrid interface which is a part of the algorithm to combine the results produced by different expert systems. Four different conditions have been prepared in laboratory environment for testing and fault detection of the algorithm. The FSM method can detect and define faults at close to 100% under all conditions. In addition, this method provides information to the user about the degree of the fault with the probability of failure.

In the construction stage of FSM-based evaluation algorithm, expert knowledge and experience are important with historical databases of the system. The performance of the algorithm depends on them as well as selected ES and AI applications. However, the FSM-based algorithm is robust against local distortions due to both measurements and evaluation results of the system, it can still reach correct conclusions on a global level. In this model, distortions on algorithms or measurement systems can be found easily by pursuing sub-matrices of the FSM and it can be improved continuously in accordance with current knowledge.

V.   Appendix

The test system has consists of a prototype (bar-winding heating transformer powered in the line voltage) whose physical characteristics such as thermal, aging, cooling performance, liquid and solid insulation, etc. are similar to power transformer as shown in Figure 9. And the other components of the system are on-line and off-line test & measurement instruments as listed in the Table 5. Multiple data acquired from the prototype is transferred to the algorithm via the converter circuits and DAQ card.

In this study, Nytro Lyra X (IEC 60296) is used as the liquid insulation and pressboard is used as solid insulation. And normal life time is considered as 20.55 years in accordance with the IEC 60076-7 standard.

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Table 1: Coefficient ranges

Linguistic terms for all expert systems	Coefficient range
No Relationship	$1\alpha = C$
Minimal Relationship	$1\alpha < C < 2\alpha$
Less Relationship	$2\alpha \leq C < 2.5\alpha$
Regular Relationship	$2.5\alpha \leq C < 3\alpha$
Strong Relationship	$3\alpha \leq C < 4\alpha$
Very Strong Relationship	$4\alpha \leq C < 5\alpha$

Table 2: Momentary evaluation (t_n) and determination of the fault probabilities

Group (4)

		1.86 1.88 4.54[1.54 1.72	3.46 2.66	1.88
T & M	[1.54 1.72	1.71]1.86	1.71][1.54 1.72 1.86	1.68 1.71]
	[1.59 1.94 1.74 1.93 4.56[1.59 1.94	3.8	[1.5 1.94 1.74	1.36
	1.29]1.74	42.15 1.299	1.93	1.29]

T & M

[1   1 1 1   1   1] [1 1 1   1   1   1 [1 1 1   1   1   1]
[1   1 1 1   1   1]
                       [1   1 1   1   1   1 [1 1 1   1   1   1]

: *Circle of conspicuous fault probability value\s belonging to a fault type* **(reliable)**

: *Circle of conspicuous fault probability value\s belonging to a fault type\s* **(not reliable)**

: *Pointer of decision vector belonging to a T&M group*

Table 3: Condition definitions and FSM results according to Table 2

Conditions	Power System Situation	T&M Reliability	Reliability of The Algorithm	FSM Results	Operation
I	Cooling problem	Completely of T&M groups are reliable	Reliable	80% probability	Needed
II*	Cooling problem	Only one T&M in the group is not reliable	Reliable	67.5% probability	Needed
III*	Cooling problem	A group of T&M is not reliable	Reliable	67.5% probability	Needed
IV	No problem	A group of T&M is not reliable	Reliable	39% probability	Not needed

* These conditions are occurred at the same time

Table 4: The FSM results for the continuous case situation of related fault/s

Power System Situation	T&M Reliability	Reliability of The Algorithm	FSM Results (Min-Max Values)	Operation
Overloading, high power loss	Completely of T&M groups are reliable	Reliable	60< probability%<100	Needed
Partial discharge	Completely of T&M groups are reliable	Reliable	60< probability%<100	Needed
Breakdown, arcing	Completely of T&M groups are reliable	Reliable	60<probability% <100	Needed
Insulating degradation, aging	Completely of T&M groups are reliable	Reliable	60< probability%<100	Needed

Cooling problem	Completely of T&M groups are reliable	Reliable	60< probability%<100	Needed
Component fault, connection failure	Completely of T&M groups are reliable	Reliable	60< probability%<100	Needed

Table 5: System components

|	
DAQ card, terminal mass / NI-USB 6251-16 bit	Input:1.25MS/sec, Output:2.00 MS/sec
Output normalization and amplifier card for the sensors & transmitters	0-10V / 0-5V
Current & Voltage transducers	50A / 500V
Kelman Transport X portable Off-line DGA device	9 gases
Hydran M2 On-line DGA device	H_2
EE36 Series; water content	Water content 0-100 ppm / 0-5V
redLINE temperature adjustment heating oven	800 Watt
PH, acidity, salinity, conductivity, particle quantity measurement device	Series 86505
Pyrometer (surface temperature measurement / portable)	Measuring range:-30/+500 ^{o}C
Supply units	0-12V , +5 /-5V, +12 / -12V
Variac	Power: 3500VA (0 - 100 %)
Prototype - bar-winding heating transformer	Power: 2500VA
Cooling fans	100 - 1500 RPM
Oil circulation pump	650 Lt/h
External heating furnace	Power: AC 220V / 1500W
Temperature control relay (on-off control)	Measuring range: -55°C to +125°C
Temperature control relay (PID control)	Inputs : TC, RTD, mV, V, mA
Pressure control valve	1-16 Bar
Boiler safety valve	1-10 Bar
Manometer	Measuring range: (0 – 10) Bar
PT100	-50 °C +400 °C
J-type thermocouple	-200 ^{o}C - 800 ^{o}C
Liquid level transducer (transmitter)	Output:4-20mA / Reed Switch
Transformer hot spot copper coil and wrapped in pressboard	(Pressboard - IEC 60554)
Liquid insulation type	Nytro Lyra X (IEC 60296)
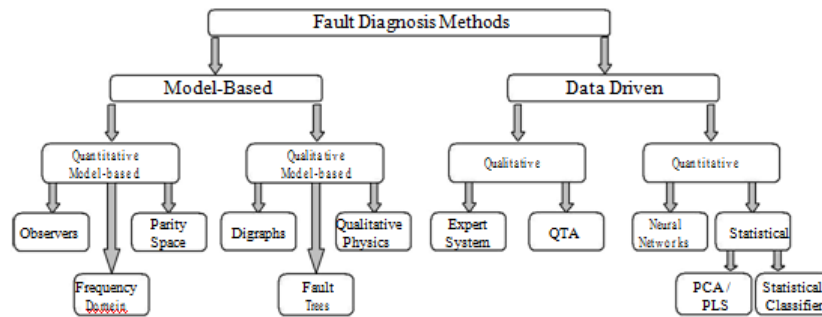
Figure 1: Classification of fault diagnosis method [17-19]
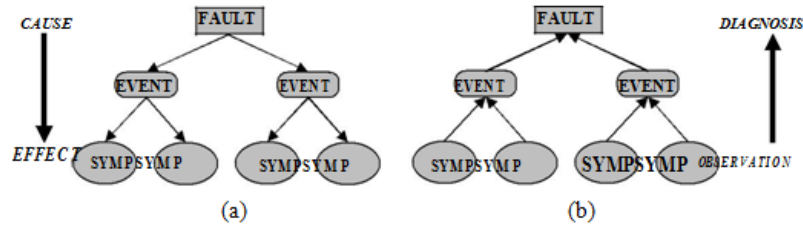

Figure 2: Fault-symptom relationship; (a) physical system, (b) diagnosis system [22]
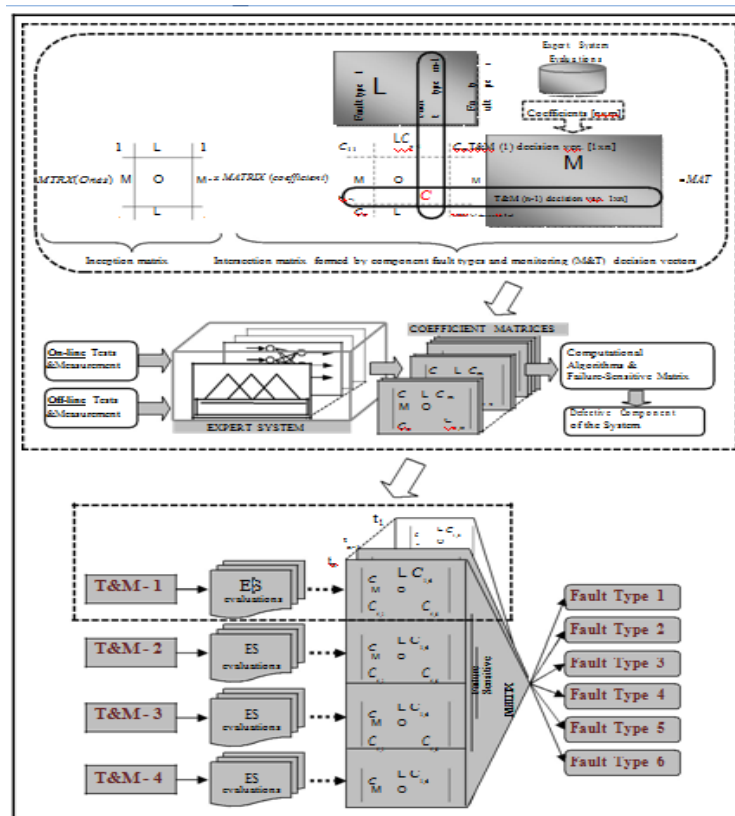

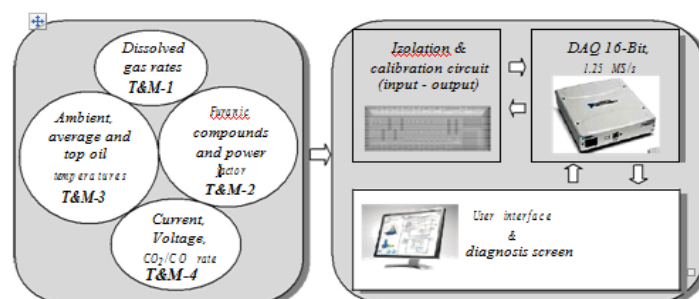Figure 3: Fault diagnosis algorithm based structure of failure-sensitive matrix

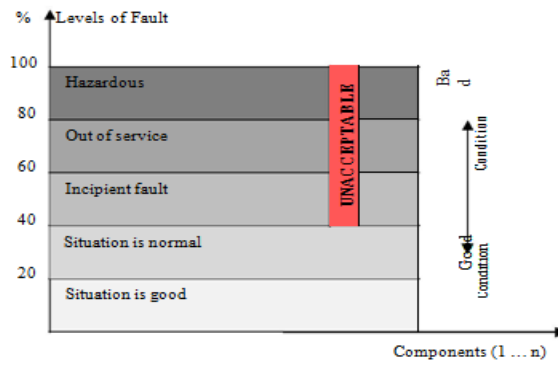Figure 4: T&M system application and evaluation interface using FSM

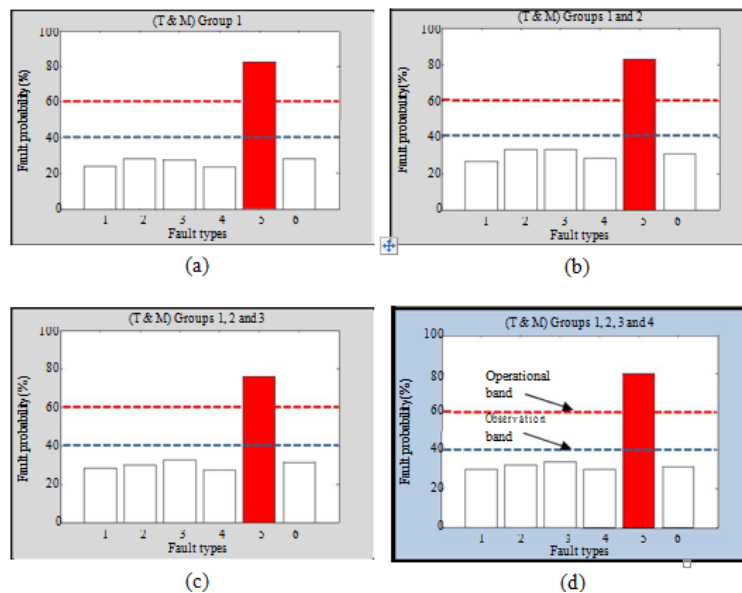Figure 5: Fault levels of components

Figure 6: Fault probabilities graphs based FSM according to evaluation of groups for condition I, (a) Group1, (b) Groups 1 and 2, (c) Groups 1, 2 and 3, (d) Groups 1 to 4
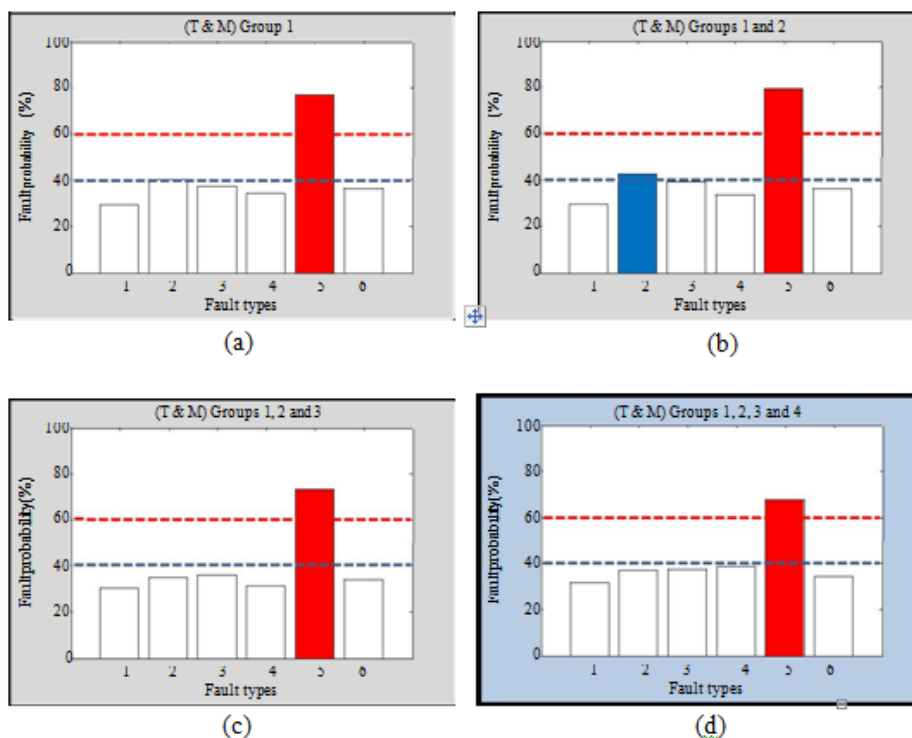

Figure 7: Fault probabilities graphs based FSM according to evaluation of groups for condition II and III, (a) Group1, (b) Groups 1 and 2, (c) Groups 1 to 3, (d) Groups 1 to 4
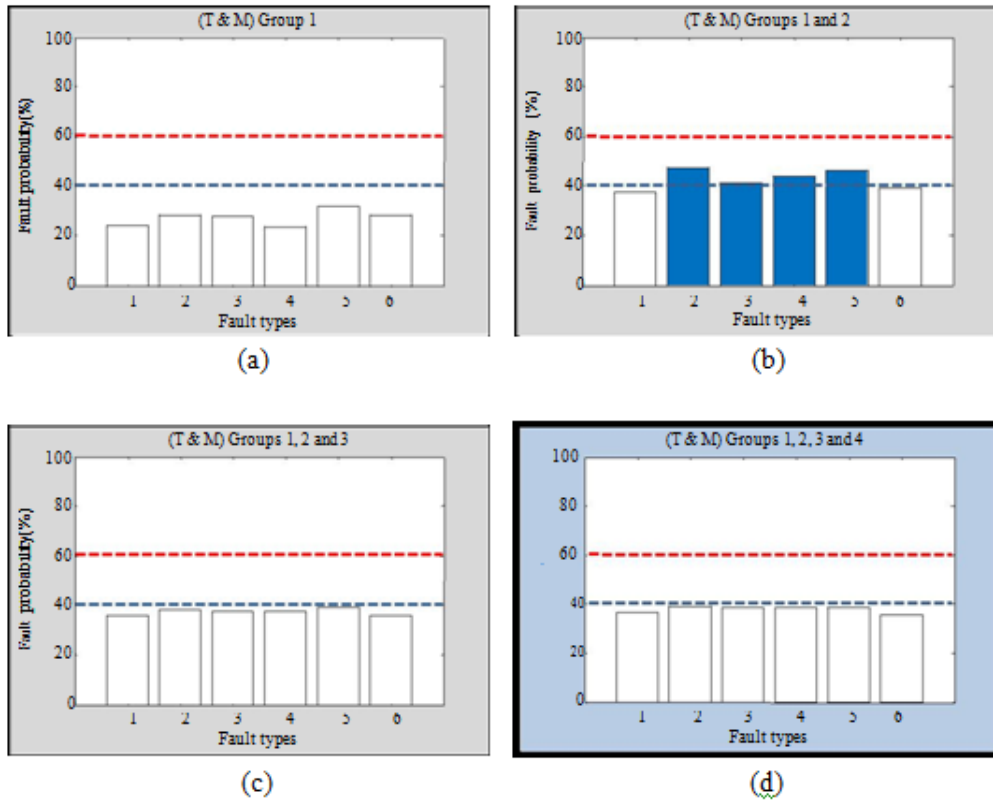
Figure 8: Fault probabilities graphs based FSM according to evaluation of groups for condition IV, (a) Group1, (b) Groups 1 and 2, (c) Groups 1, 2 and 3, (d) Groups 1 to 4

Figure 9: Prototype and test system vironment 37